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A Data Mining Approach for Analysis of a Wire Electrical Discharge Machining Process

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Abstract
Wire electrical discharge machining (WEDM) is a non-conventional material-removal process where a continuously travelling electrically conductive wire is used as an electrode to erode material from a workpiece. To explore its fullest machining potential, there is always a requirement to examine the effects of its varied input parameters on the responses and resolve the best parametric setting. This paper proposes parametric analysis of a WEDM process by applying non-parametric decision tree algorithm, based on a past experimental dataset. Two decision tree-based classification methods, i.e. classification and regression tree (CART) and Chi-squared automatic interaction detection (CHAID) are considered here as the data mining tools to examine the influences of six WEDM process parameters on four responses, and identify the most preferred parametric mix to help in achieving the desired response values. The developed decision trees recognize pulse-on time as the most indicative WEDM process parameter impacting almost all the responses. Furthermore, a comparative analysis on the classification performance of CART and CHAID algorithms demonstrates the superiority of CART with higher overall classification accuracy and lower prediction risk.

Keywords
wire electrical discharge machining, data mining, classification and regression tree, chi-squared automatic interaction detection, classification.

Introduction

In present day manufacturing industries, wire electrical discharge machining (WEDM) process has become quite popular due to its competence to machine various tough and hard-to-machine materials with complex shape geometries and close tolerances. The WEDM is a variant of electrical discharge machining (EDM) process where a continuously travelling electrically conductive wire (e.g. tungsten, brass or copper with diameter between 0.05 and 0.3 mm) is used as the electrode. This wire is kept in tension using a mechanical device and its movement is numerically controlled so as to attain the desired accuracy and tolerance while machining a given workpiece. In WEDM process, removal of material usually occurs due to complex erosion effect of expeditious, continual and distinct spark discharges between the wire tool and the workpiece submerged in kerosene or deionized water (dielectric medium). These electrical discharges cause melting and vaporization of tiny amounts of material from the workpiece, which are rinsed away by the dielectric, causing small pits on the workpiece. In WEDM process, as the material is abraded before the wire and as there is no direct contact between the workpiece and the wire, chances of generation of stress, chatter and vibration during the machining operation are less (Ho et al., 2004; Mandal and Dixit, 2014). As WEDM is distinguished to be a highly accurate process, it has now found wide-ranging applications in aerospace, nuclear, automotive, bio-medical, and tool and die-making industries. It can machine various unusual high-strength-temperature-resistive materials, like alloys, titanium, cemented carbides, ceramics and silicon (Patel and Vaghmare, 2013). In a manufacturing industry, the main goal of WEDM application is to realize higher machining rate (MR) along with better dimensional accurateness and surface characteristic. However, the performance of a WEDM process re-

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garding material removal rate (MRR), surface roughness (SR), wire wear ratio (WWR), kerf width, dimensional deviation (DD) etc. is often observed to be influenced by several controllable (input) parameters, like peak current (I_p) (in A), pulse-on time (T_{on}) (in µs), pulse-off time T_{off}) (in µs), wire tension (WT) (in g), wire feed rate (WF) (in m/min), spark gap voltage (SV) (in V) etc. The presence of an extensive set of process parameters, stochastic nature of the process, possible interactions between the process parameters and conflicting behaviour of the responses make it imperative to explore the effects of various WEDM process parameters on the outputs. Thus, to accomplish the desired response values, identification of the optimal machining parameters and their settings plays a significant role. It has been observed that inaccurately selected WEDM process parameters may often lead to short-circuiting of wire, breakage of wire and damage of the workpiece surface. With the rapidly growing use of WEDM process for machining newer and advanced engineering materials, an ardent need is thus acknowledged for development and deployment of an innovative approach for studying the impacts of varied process parameters on the responses and identifying the parametric mix leading to optimization of WEDM process. From the review of the contemporary literature (Kumar et al., 2013; Lal et al., 2015; Dabade and Karidkar et al., 2016; Lusi et al., 2016; Manjaiah et al., 2016; Arikatla et al., 2017; Ramanan and Elangovan, 2018; Devarajaiah and Muthumari, 2018; Vignesh and Ramanujam, 2018; Srinivasarao and Suneel, 2018; Nayak et al., 2018), it has been revealed that determination of the optimal parametric mixes for WEDM processes has already caught the attention of the past researchers, and numerous multi-objective optimization techniques, like grey-Taguchi method, desirability function approach, technique for order of preference by similarity to ideal solution (TOPSIS), evolutionary algorithms etc. have been applied. But, the applications of various data mining tools for studying the influences of varying WEDM process parameters on the responses and identifying the optimal combinations of those process parameters are really limited. Thus, this paper focuses on the application of data mining techniques, primarily through decision trees, to fulfil the above-mentioned objectives. Two decision tree-based classification algorithms, i.e. classification and regression tree (CART) and Chi-squared automatic interaction detection (CHAID) are thus employed here, and their performance is contrasted with respect to overall classification accuracy and prediction risk.

Data mining

Data mining, occasionally known as 'knowledge discovery in databases', is the procedure of drilling through data to unveil hidden patterns or connections and anticipate future trends (Tan et al., 2006; Han et al., 2012). It mainly depends on effective collection of data and warehousing as well as computer processing. The application of data mining has strong relations with statistics (to study data relationships), artificial intelligence (to provide human-like intelligence) and machine learning (to learn from data to make predictions). Data mining thus allows to (a) filter all the chaotic and repetitive noise in the dataset, (b) predict automatic pattern based on trend and behaviour analysis, (c) envisage the likely outcomes, (d) create decision-oriented information, (e) accelerate the pace of making informed decisions, (f) focus on large dataset and database for analysis, and (g) form clusters based on visually documented groups of facts. In predictive modelling, the primary objective is to approximate the value of a specific target attribute from a set of training data where the attribute values are established beforehand. Classification is a unique example of predictive modelling where a data set is already segmented into pre-specified groups and patterns are identified in the data to distinguish those groups. The explored patterns can then be adopted to categorize another dataset where the appropriate group description for the target attribute is unknown. Regression analysis is also an example of predictive modelling with numerical target attribute and the objective is to envision that value for new data. The application of data mining techniques follows some procedural steps, such as (a) data cleaning (elimination of noisy and outlier data), (b) data assimilation (amalgamation of multiple data sources), (c) data selection (recovery of pertinent data from the database), (d) data conversion (conversion of data for mining purposes), (e) data mining (identification of data patterns), (f) pattern assessment (extraction of attractive patterns) and (g) knowledge display (picturing of the mined information) (Ramani et al., 2020).

Decision tree analysis

The decision tree analysis can be defined as a set of practices to estimate and show the extant relations between a dependent variable and a class of independent variables. It is based on consecutive partitioning algorithm to continuously split the data to constitute homogeneous subsets, producing a hierarchical tree consisting of decision rules convenient for data anticipation or classification. The main classification methods for decision tree induction are CART and CHAID algorithms, and their characteristics are outlined as below:

1. The resultant hierarchy is known as a tree and a particular section is referred to as a node.
2. The root node consists of the entire database.
3. It is branched conclusively forming child nodes.
4. The final subgroups are known as terminal nodes or leaves when no further data classification is possible.
5. There are three primary elements to be defined to implement them, i.e. a set of questions delimitating data apportionment, a criterion to institute the best division to develop child nodes and a completion rule for the classifications (stop-splitting rule).

Both of them build decision trees, where each (non-terminal) node establishes a split condition to produce an optimal prediction for continuous dependent variables or classification for categorical dependent variables.

CART-based algorithm

Breiman et al. (1993) proposed this classification algorithm for origination of decision trees. It divides a particular population into binary splits, while consecutively breaking up the data into smallest components with maximal homogeneity with regard to the dependent variable. It follows a sequential procedure, as enlisted below:

1. Tree growing process – This algorithm evaluates all the possible splits of the explanatory variables and designates the 'best' split, beginning with the root node. Thereafter, this process is imitated for consequent nodes. The 'best' split is explained by the minimal overall impurity. Usually, in this algorithm, univariate splits are only designed. Hence, beginning with the root node, a tree is developed in the downward direction by repeatedly performing the splitting operation.
2. Splitting criterion and impurity measure – At a particular node, the 'best' split is considered for maximization of a specific splitting criterion. For a specific impurity measure for a node, the splitting criterion conforms to decrement in impurity. The 'Gini' index is adopted as the impurity function in this algorithm. The chosen independent variable is that one which assures a segmentation having the maximum level of improvement.
3. Stopping rule – The tree growing process would stop while satisfying any of the following stopping rules:
   i) When all cases in a particular node have same values of the dependent variable.
   ii) When the present tree depth arrives the maximum limit as stated by the user.
   iii) When the node size is smaller than the minimum size as stated by the user.
   iv) When the node splitting forms a child node having size smaller than the user-identified minimum size.
4. Variable importance – The importance measure of an explanatory variable X in the developed tree is stated as the sum across all the splits in the tree showing the gains that X achieves when it is adopted as a dominant or surrogate splitter. The importance of variable X is denoted with respect to a normalized quantity as compared to the variable having the maximum measure of importance. Its value spans between 0 and 100, having the variable with the largest measure of importance score as 100. Thus, an explanatory variable's importance is a preferred indicator to account the significance of disaggregated variable as well as aggregated variable (which has already appeared in the decision tree).

CHAID-based algorithm

This algorithm, proposed by Kass (1980), generates non-binary decision trees (with more than two branches connected to a single node) based on the Bonferroni's test. It proceeds through the following three stages:

1. Merging – For each dependent variable X, combine the non-significant categories. Each final category of X results in one child node if X is utilized to divide the node. This merging step also estimates the revised p-value to be subsequently used for splitting purpose.
2. Splitting – The explanatory variable having the lowest significant p-value is identified as the best and the group is divided based on this predictor. The group is not divided when no predictor has a significant p-value.
3. Stopping – These stages are imitated till all the subgroups have either been inspected or have encompassed too few observations. The adopted stopping rules are mostly the same as those already mentioned for CART algorithm.

Development of decision trees for WEDM process

In a four-axis CNC WEDM set-up, Kumar et al. (2013) performed 54 experiments to investigate the effects of six process parameters, e.g. T_{on}, T_{off}, I_P, SV, WF and WT on four responses. The responses were MR (in mm/min), SR (in µm), DD (in µm) and WWR. Other factors, like type of the workpiece material (pure titanium-grade 2), wire electrode (brass wire having diameter 0.25 mm), workpiece thickness and pressure of the dielectric were kept constant during the experimental runs. Table 1 exhibits the detailed experimental plan and measured values of the responses. Among these responses, MR is the sole beneficial quality characteristic desired with its higher value. On the contrary, minimum values are required for SR, DD and WWR (non-beneficial attributes (Sarker and Chakraborty, 2021).

Table 1
Experimental observations for the WEDM process (Kumar et al., 2013)

Run No.	I_p	T_{on}	SV	T_{off}	WF	WT	SR	WWR	MR	DD
1	200	120	50	50	7	500	3.22	0.095	1.14	160
2	160	116	50	56	4	500	2.48	0.063	0.576	150
3	160	112	60	50	4	950	2.23	0.079	0.42	145
4	120	116	50	44	10	950	2.75	0.086	0.954	159
5	120	116	60	50	7	500	2.47	0.061	0.544	152
6	160	120	40	50	4	950	2.93	0.088	1.075	162
7	160	116	50	56	10	1400	2.48	0.063	0.586	150
8	160	116	50	50	7	950	2.65	0.080	0.695	152
9	160	116	50	44	4	500	2.81	0.089	1.014	160
10	160	120	40	50	10	950	2.94	0.088	1.075	160
11	160	120	40	56	7	950	2.91	0.087	0.995	160
12	160	120	60	50	4	950	2.83	0.079	0.809	159
13	160	116	50	44	10	500	2.79	0.076	1.012	160
14	160	116	50	50	7	950	2.61	0.064	0.573	150
15	120	112	50	50	7	500	2.49	0.048	0.406	145
16	160	116	50	50	7	950	2.68	0.082	0.697	152
17	120	116	60	50	7	1400	2.49	0.059	0.538	150
18	160	112	40	56	7	950	2.32	0.060	0.48	145
19	120	116	50	56	10	950	2.31	0.056	0.535	151
20	200	116	40	50	7	1400	2.89	0.079	0.825	152
21	200	116	60	50	7	500	2.69	0.072	0.773	152
22	200	116	50	56	10	950	2.57	0.074	0.792	153

Table 1 [cont.]

Run No.	I_p	T_{on}	SV	T_{off}	WF	WT	SR	WWR	MR	DD
23	120	116	40	50	7	1400	2.71	0.068	0.625	152
24	120	112	50	50	7	1400	2.51	0.054	0.425	145
25	200	116	50	56	4	950	2.56	0.078	0.799	155
26	160	120	60	50	10	950	2.82	0.081	0.81	153
27	120	120	50	50	7	500	2.77	0.074	0.83	158
28	160	112	40	50	10	950	2.35	0.085	0.521	150
29	200	112	50	50	7	500	2.48	0.083	0.535	150
30	160	112	40	44	7	950	2.70	0.089	0.858	153
31	200	112	50	50	7	1400	2.51	0.082	0.54	150
32	160	116	50	50	7	950	2.65	0.081	0.658	150
33	200	116	50	44	4	950	2.88	0.092	1.02	159
34	160	116	50	50	7	950	2.65	0.081	0.656	152
35	160	120	40	44	7	950	3.28	0.107	1.28	165
36	200	116	50	44	10	950	2.98	0.095	1.03	160
37	200	116	40	50	7	500	2.84	0.079	0.829	155
38	160	112	40	50	4	950	2.33	0.081	0.529	150
39	160	116	50	56	10	500	2.50	0.064	0.589	150
40	160	116	50	50	7	950	2.69	0.081	0.659	152
41	160	120	60	56	7	950	2.66	0.070	0.792	153
42	160	112	60	44	7	950	2.60	0.081	0.495	150
43	200	116	60	50	7	1400	2.68	0.072	0.778	155
44	120	116	50	44	4	950	2.75	0.086	0.959	155
45	160	112	60	50	10	950	2.28	0.079	0.429	145
46	120	120	50	50	7	1400	2.75	0.074	0.823	158
47	160	112	60	56	7	950	2.15	0.064	0.395	140
48	160	116	50	44	4	1400	2.85	0.088	0.981	159
49	120	116	40	50	7	500	2.78	0.068	0.635	158
50	160	120	60	44	7	950	3.00	0.085	1.00	159
51	120	116	50	56	4	950	2.29	0.060	0.541	150
52	200	120	50	50	7	1400	3.12	0.091	1.052	159
53	160	116	50	44	10	1400	2.82	0.088	0.962	155
54	160	116	50	56	4	1400	2.49	0.060	0.592	150
Median							0.74	2.68	152	0.079

In this paper, CART and CHAID algorithms are applied to explore the experimental dataset of Kumar et al. (2013) while generating the corresponding decision trees and induction rules to study the influences of the considered WEDM process parameters on the four responses. An endeavour is also put forward to compare their relative classification performance with respect to prediction accuracy and prognosis risk. In a decision tree, an internal node denotes a test on an attribute, a branch characterizes the result of the test and a leaf node depicts a class label. A specific decision or induction rule can thus be obtained while following the direction from the root to leaf node. For development of the related decision trees using CART and CHAID algorithms (available in SPSS 16.0), the following specifications are predefined.

For CART algorithm:

Growing method: CART, Categorical dependent variables: MR, SR, DD and WWR, Continuous independent variables: T_{on}, T_{off}, I_P, SV, WF and WT, Number of sample folds: 3, Validation: Cross validation, Growth limit: Maximum depth of tree = 5, Minimum number of cases: Parent node = 3, Child node = 2, Impurity measure: 'Gini', Minimum shift in improvement = 0.0001.

For CHAID algorithm:

Growing method: CHAID, Categorical dependent variables: MR, SR, DD and WWR, Categorical independent variables: T_{on}, T_{off}, I_P, SV, WF and WT,

Validation: Cross validation, Growth limit: Maximum depth of tree = 5, Number of sample folds: 3, Minimum number of cases: Parent node = 3, Child node = 2, Significance level for: a) Splitting node = 0.03, b) Merging categories = 0.05 and c) Chi-square statistic = Pearson, Model estimation: a) Maximum number of iterations = 100, b) minimum variation in expected cell frequencies = 0.001 and c) Modify significance values based on the Bonferroni method.

Figure 1 exhibits the CART algorithm-based decision tree, showing the impacts and contributions of the six WEDM process parameters on MR. In this figure, the term 'low' belongs to observations with MR $\leq$ 0.74 mm/min and 'high' refers to those observations having MR $>$ 0.74 mm/min (where 0.74 mm/min is the median value of MR). This classification tree contains 5 splits and 6 terminal nodes. The classification process begins with the top or root node with level 0. All the 54 observations are first assigned to this node where 27 observations are equally classified as 'low' and 'high', as represented in this node. The root node is again divided into two new nodes and the related split condition is shown below the root node. It can be noticed from this decision tree that during the first classification, 42 experimental observations with T_{on} less than or equal to 118 µs are routed to node number 1, categorized as 'low' items. The remaining 12 observations with T_{on} greater than 118 µs are directed to node number 2 with 'high' classification. All the 12 observations belonging to only 'high' value identify node 2 as a pure node with no misclassification error. In node 1, unequal number of observations rec-

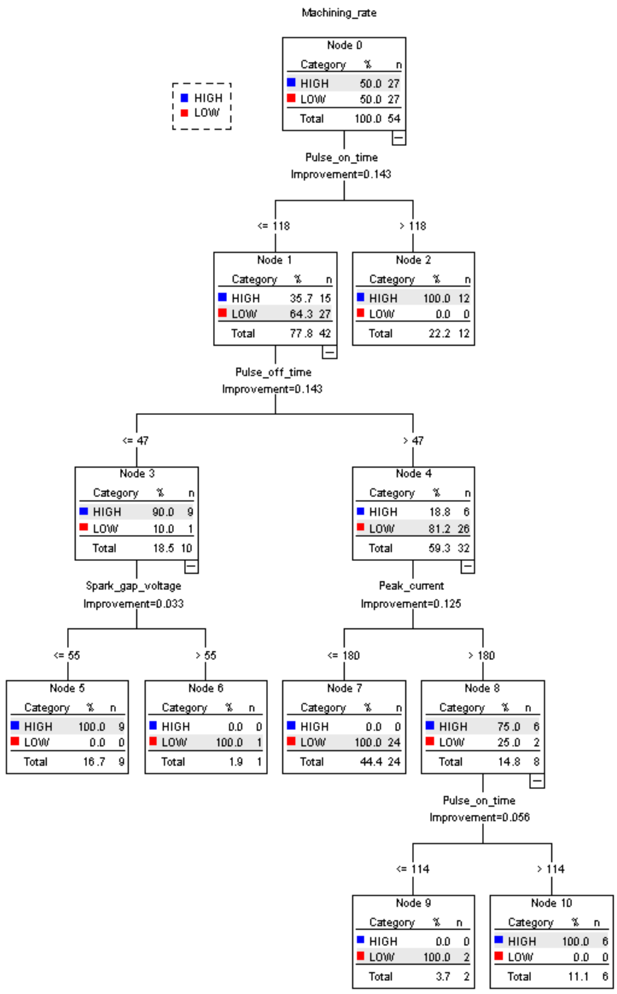

Fig. 1. Decision tree depicting the impacts of WEDM process parameters on MR

ognizes it as an impure node providing more child nodes. Thus, node 1 is now split giving rise to two impure nodes. In this split, 10 observations with T_{off} less than or equal to 47 µs are dispatched to node number 3, and the rest 32 observations with T_{off} greater than 47 µs are directed to node number 4. Now, based on the values of SV, node 3 is consequently divided into two pure nodes. In this split, nine observations with SV less than or equal to 55 V are attached to node number 5 with 'high' values of classification, and only one observation with SV greater than 55 V is routed to node number 6 with 'low' classification value. Similarly, another splitting is carried out from node 4 based on I_P. In this split, 24 observations with I_P less than or equal to 180 A are dispatched to node number 7 with 'low' categorization, and the remaining eight observations with I_P greater than 180 A are sent to node number 8. From node number 8, two pure nodes again emerge out based on the values of

T_{on}. In this splitting operation, two observations having T_{on} less than or equal to 114 µs are routed to node number 9 and the rest six observations with T_{on} greater than 114 µs are sent to node number 10. In this decision tree, it is noticed that all the terminal nodes are pure representing no misclassification error. The percentage of correct classification at each of the terminal nodes is presented in Table 2. Now, from this tree, the following decision/induction rules can be structured to envisage the impacts of various WEDM process parameters on MR.

Table 2
Percentage of correct classification of MR based on CART algorithm

Classification	Terminal node	MR			
		Low ($\leq$ 0.74 mm/min)		High (> 0.74 mm/min)	
		Number of observations	%	Number of observations	%
1	Node 2	0	0	12	100
2	Node 5	0	0	9	100
3	Node 6	1	100	0	0
4	Node 7	24	100	0	0
5	Node 9	2	100	0	0
6	Node 10	0	0	6	100

Decision rules for MR based on CART:
Rule 1: If $T_{on} > 118$ µs Then MR is (0.74–1.28]
$[P = 100\%,\ Q = 44.44\%,\ C = 22.22\%,\ QTY = 12]$
$[T = 166.67\%]$
Rule 2: If $T_{on} \leq 118$ µs and $T_{off} \leq 47$ µs and SV ≤ 55 V Then MR is [0.74–1.28]
$[P = 100\%,\ Q = 33.33\%,\ C = 16.67\%,\ QTY = 9]$
$[T = 150\%]$
Rule 3: If $T_{on} \leq 118$ µs and $T_{off} \leq 47$ µs and SV > 55 V Then MR is [0.40–0.74]
$[P = 100\%,\ Q = 3.70\%,\ C = 1.85\%,\ QTY = 1]$
$[T = 105.55\%]$
Rule 4: If $T_{on} \leq 118$ µs and $T_{off} > 47$ µs and $I_P \leq 180$ A Then MR is [0.40–0.74]
$[P = 100\%,\ Q = 88.88\%,\ C = 44.44\%,\ QTY = 24]$
$[T = 233.32\%]$
Rule 5: If $T_{on} \leq 118$ µs and $T_{off} > 47$ µs and $I_P > 180$ A and $T_{on} \leq 114$ µs Then MR is [0.40–0.74]
$[P = 100\%,\ Q = 7.41\%,\ C = 3.70\%,\ QTY = 2]$
$[T = 111.11\%]$
Rule 6: If $T_{on} \leq 118$ µs and $T_{off} > 47$ µs and $I_P > 180$ A and $T_{on} > 114$ µs Then MR is [0.74–1.28]
$[P = 100\%,\ Q = 22.22\%,\ C = 11.11\%,\ QTY = 6]$
$[T = 133.33\%]$,

where P is the rule confidence, Q is the percentage of items in current equivalence class conforming to a rule, C is the rule support, QTY is the number of observations corresponding to a rule and T (total strength) = (P + Q + C) (Agarwal et al., 2019).

Among the developed decision rules, rule 4 with the maximum total strength of 233.32 states that in the considered WEDM process, when T_{on} is less than or equal to 118 µs, T_{off} is greater than 47 µs and I_P is less than or equal to 180 A, the corresponding MR would be low. On the other hand, rule 1 with a total strength 166.67 reveals that high T_{on} leads to high MR. As MR is a beneficial response, it is thus advised to operate the WEDM process at high setting of T_{on} (above 118 µs).

In CART-based decision tree, where univariate splits are considered, the predictor variables are usually rated on a 0–100 scale depending on their preference in accounting for the responses on the dependent variable (MR). It can be noticed from Fig. 2 that T_{on} has the maximum influence on MR response, followed by T_{off}, I_P and SV. In this WEDM process, MR is observed to be totally unaffected by WF and WT.

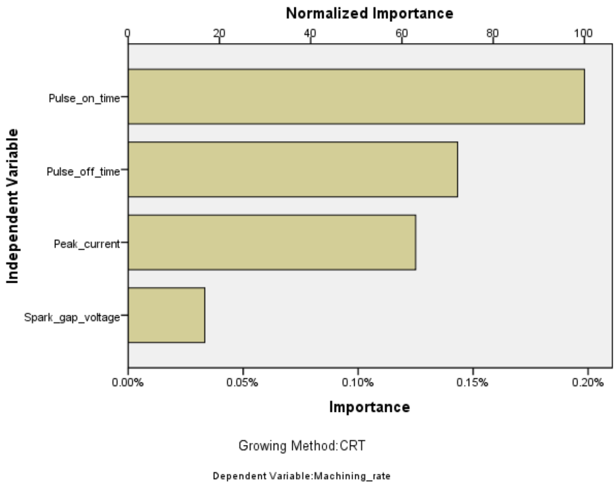

Fig. 2. Importance of various WEDM process parameters on MR

Similarly, the developed decision tree for MR using CHAID algorithm is exhibited in Fig. 3. As compared to CART algorithm, same number of classifications is also obtained in CHAID algorithm. In this multi-split decision tree, node 7 contains non-homogenous observations, identifying it as an impure node with 1.85% misclassification error. The corresponding decision rules identify T_{on}, T_{off} and I_P as the most indicative WEDM process parameters influencing MR, whereas, SV, WF and WT appear to be insignificant parameters.

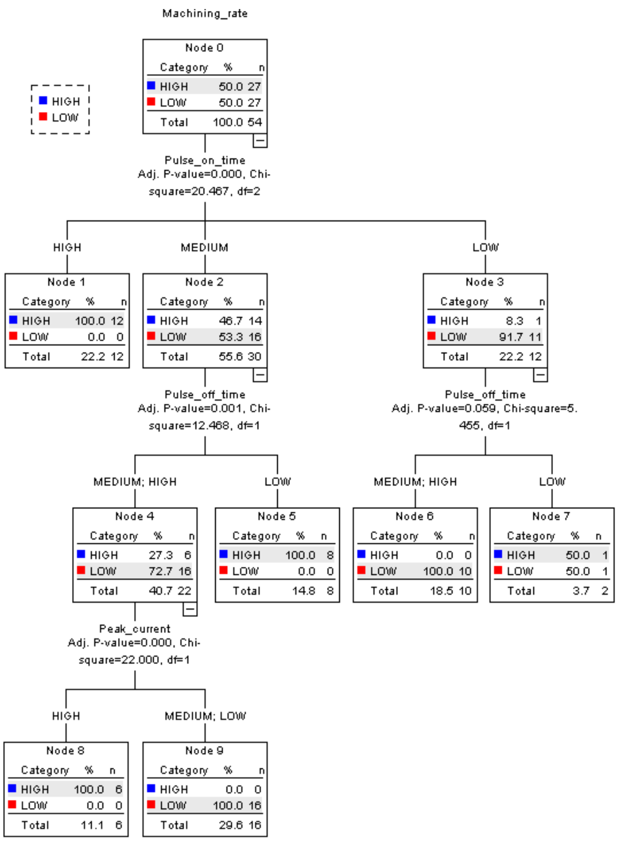

Fig. 3. CHAID algorithm-based decision tree for MR

Decision rules for MR based on CHAID:
Rule 1: If T_{on} = High Then MR is (0.74-1.28]
[P = 100%, Q = 44.44%, C = 22.22%, QTY = 12]
[T = 166.66%]
Rule 2: If T_{on} = Medium and T_{off} = Low Then MR is [0.74–1.28]
[P = 100%, Q = 29.62%, C = 14.81%, QTY = 8]
[T = 144.43%]
Rule 3: If T_{on} = Low and T_{off} = Low Then MR is [0.74–1.28]
[P = 100%, Q = 37.04%, C = 18.52%, QTY = 10]
[T = 155.56%]
Rule 4: If T_{on} = Low and T_{off} = Medium or High Then MR is [0.40–0.74]
[P = 50%, Q = 3.70%, C = 1.85%, QTY = 1]
[T = 55.55%]
Rule 5: If T_{on} = Medium and T_{off} = Medium or High and I_P = High Then MR is [0.74–1.28]
[P = 100%, Q = 22.22%, C = 11.11%, QTY = 6]
[T = 133.33%]
Rule 6: If T_{on} = Medium and T_{off} = Medium or High and I_P = Medium or Low Then MR is [0.40–0.74]
[P = 100%, Q = 59.26%, C = 29.63%, QTY = 16]
[T = 188.89%]

The CART algorithm-based decision tree representing the influences of varied WEDM process parameters on SR is depicted in Figure 4. In this case, the measured SR values are also assorted into two classes, i.e. 'low' containing SR values ≤ 2.68 µm and 'high' has SR values > 2.68 µm (where 2.68 µm is the median SR value). The induction rules formulated from the developed decision tree state that when T_{on} is greater than 118 µs, the resulting SR would be high. It can also be highlighted from the developed rules that when T_{on} is less than or equal to 118 µs, T_{off} is greater than 47 µs and SV is greater than 45 V, the SR would be low. The rules extracted from the decision tree developed using CHAID algorithm, as exhibited in Fig. 5, also prove that high T_{on} results in high SR. Medium or low T_{off} is also responsible for

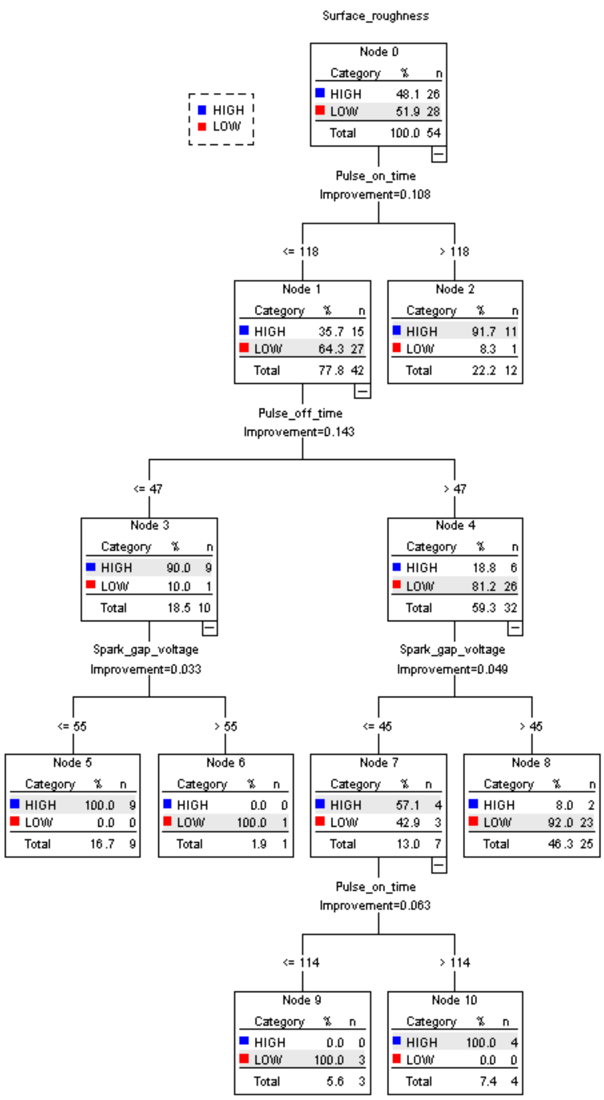

Fig. 4. Decision tree for SR using CART algorithm

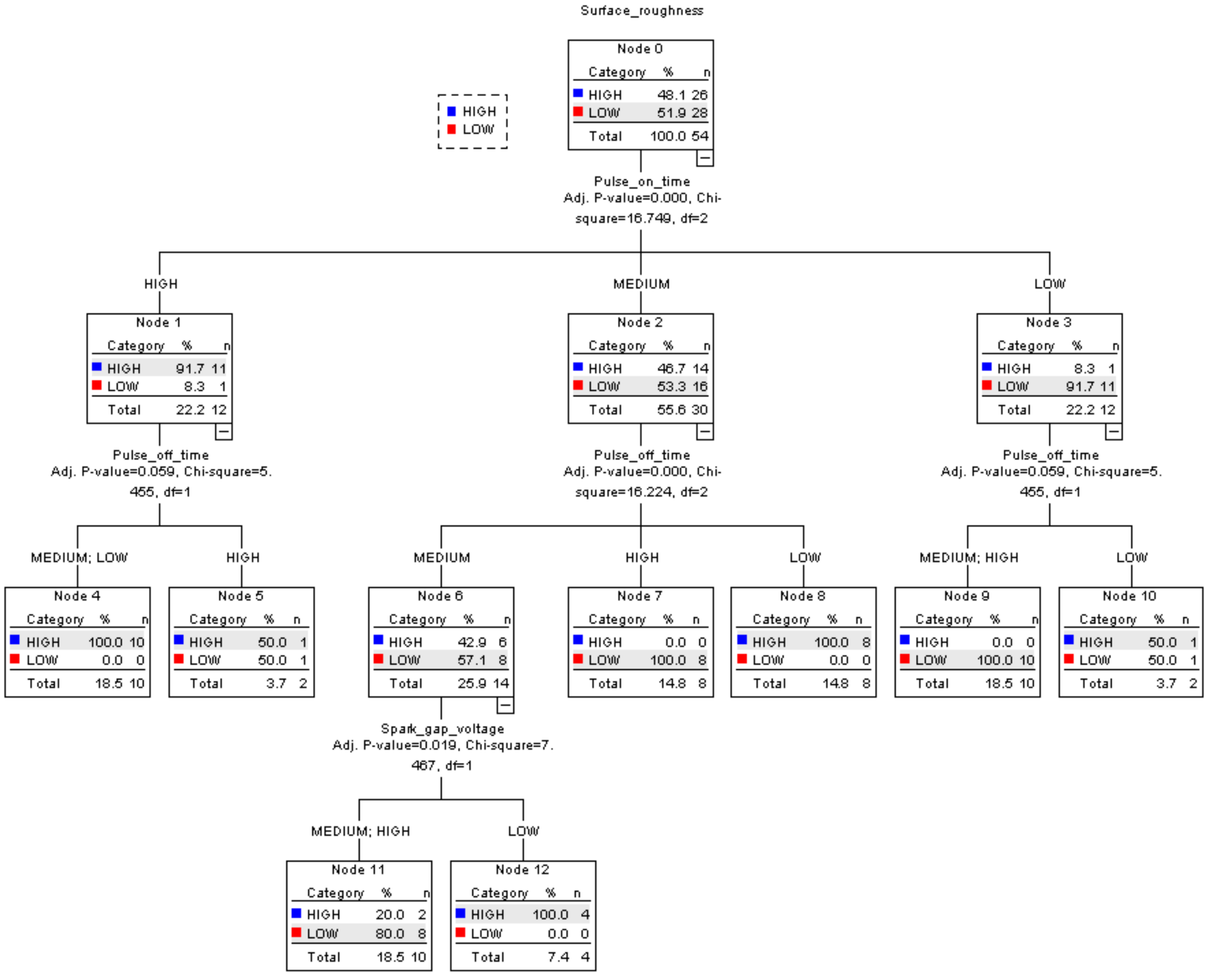

Fig. 5. CHAID algorithm-based decision tree for SR

increased SR. Similarly, low SV is responsible for high value of SR. In both the sets of rules developed using CART and CHAID algorithms, WF and WT appear to be irrelevant WEDM process parameters having no influences on SR.

Figure 6 depicts the relative importance of various WEDM process parameters on SR. It can be revealed from this figure that T_{on} plays the dominant role in controlling SR of the machined components, followed by T_{off} and SV. The other three process parameters, i.e. WF, I_P and WT have less importance on SR.

To visualize the effects of various WEDM process parameters on DD response, the decision tree is now generated using CART algorithm. When the values of DD are less than or equal to 152 µm, they are denoted as 'low' and when its values are greater than 152 µm, they are designated as 'high' (where 152 µm is the median of DD). The 'If-Then' rules extracted from this decision tree highlight that T_{on} less than or equal to 118 µs, T_{off} greater than 47 µs and I_P less than or equal to 180 A always lead to lower DD. Higher T_{on} is liable for higher DD. Low T_{on}, high T_{off} and low SV would cause lower DD.

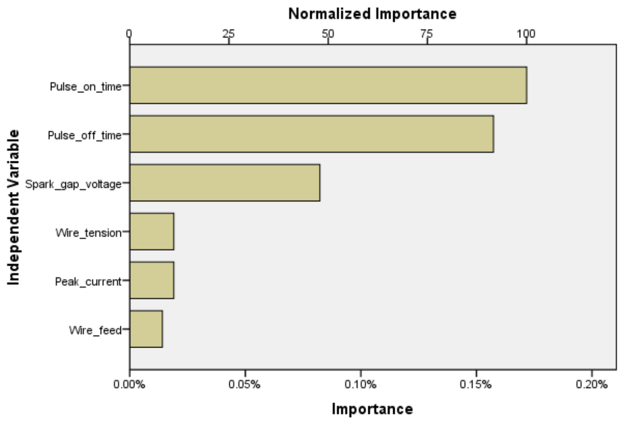

Fig. 6. Importance of various WEDM process parameters on SR

The induction rules generated based on CHAID algorithm also confirm these observations. Combining both the sets of decision rules from CART and CHAID algorithms, the optimal parametric mix of low T_{on}, medium or high T_{off}, low I_P and high SV would always lead to lower DD. Kumar et al. (2013) also observed that almost the same combination of the input parameters would be responsible for attaining lower DD in the said WEDM process. The importance plot of Fig. 7 identifies T_{on} as the most critical WEDM process parameter affecting DD, followed by T_{off}, I_P and SV. Interestingly, WF and WT have no significant roles in controlling the DD of the machined components.

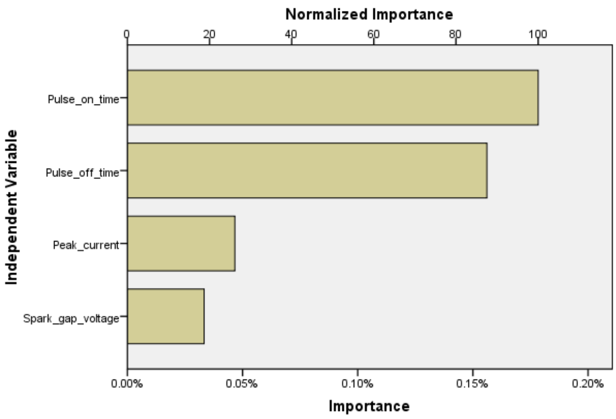

Fig. 7. Importance of varied WEDM process parameters on DD

Decision rules for DD using CART:
Rule 1: If $T_{on} > 118$ µs Then DD is [152–165]
[P = 100%, Q = 46.15%, C = 22.22%, QTY = 12]
[T = 168.37%]
Rule 2: If $T_{on} \le 118$ µs and $T_{off} \le 47$ µs and SV ≤ 55 V Then DD is [152–165]
[P = 100%, Q = 34.61%, C = 16.67%, QTY = 9]
[T = 151.28%]
Rule 3: If $T_{on} \le 118$ µs and $T_{off} \le 47$ µs and SV > 55 V Then DD is [140–152]
[P = 100%, Q = 3.57%, C = 1.85%, QTY = 1]
[T = 105.42%]
Rule 4: If $T_{on} \le 118$ µs and $T_{off} > 47$ µs and $I_P \le 180$ A Then DD is [140–152]
[P = 95.80%, Q = 82.14%, C = 52.60%, QTY = 23]
[T = 230.54%]
Rule 5: If $T_{on} \le 118$ µs and $T_{off} > 47$ µs and $I_P > 180$ A and $T_{on} > 114$ µs
Then DD is [152–165]
[P = 66.67%, Q = 15.38%, C = 7.41%, QTY = 4]
[T = 89.46%]
Rule 6: If $T_{on} \le 118$ µs and $T_{off} > 47$ µs and $I_P > 180$ A and $T_{on} \le 114$ µs
Then DD is [140–152]
[P = 100%, Q = 7.14%, C = 3.70%, QTY = 2]
[T = 110.84%]

The decision tree for WWR originated using CART algorithm is shown in Fig. 8. The corresponding

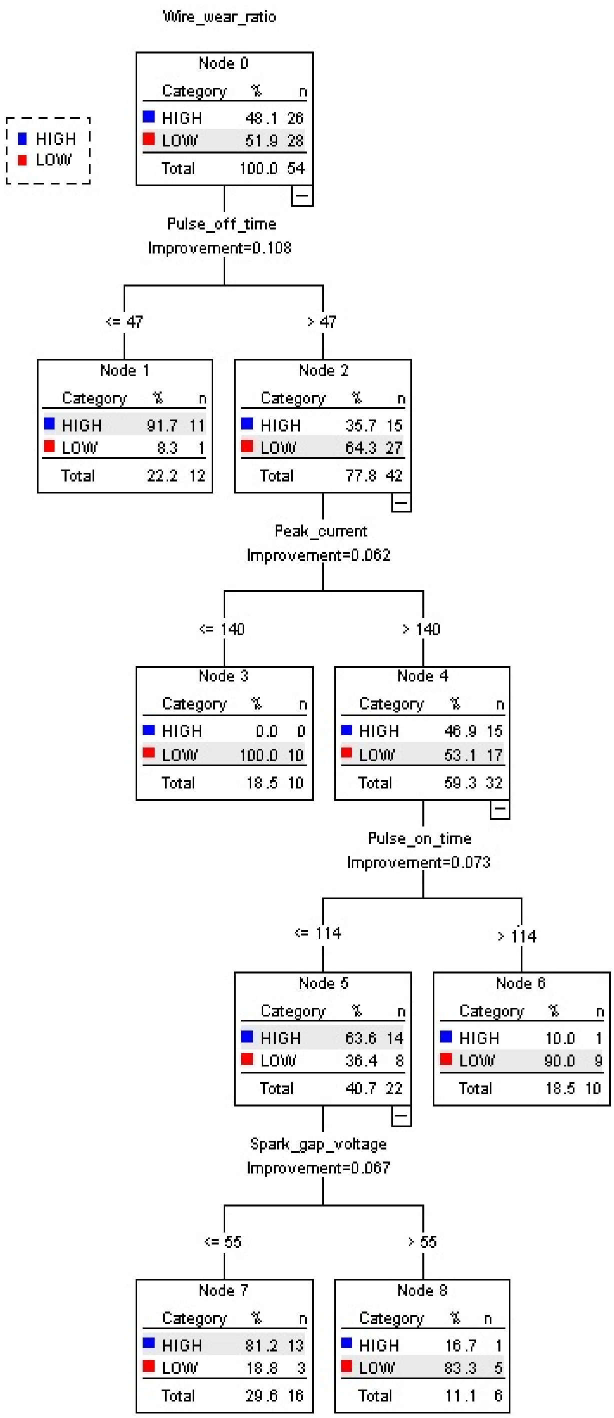

Fig. 8. Decision tree for WWR using CART algorithm

'If-Then' rules are subsequently generated from it. When the values of WWR are less than or equal to 0.079, they are denoted as 'low' and when its values are greater than 0.079, they are designated as 'high' (where 0.079 is the median of WWR. An analysis of these rules reveals that when T_{off} time is greater than 47 µs and I_P is less than or equal to 140 A, the achievable WWR is low. Similarly, lower T_{off} leads to higher WWR. The rules extracted from the decision tree based on CHAID algorithm, as shown in Fig. 9, state that T_{off} would considerably affect WWR. On the contrary, WT is least responsible for attaining lower WWR. From Fig. 10, T_{off} is identified as the most indicative parameter influencing WWR, followed by SV, I_P and T_{on}. WF and WT appear to be insignificant WEDM process parameters for WWR.

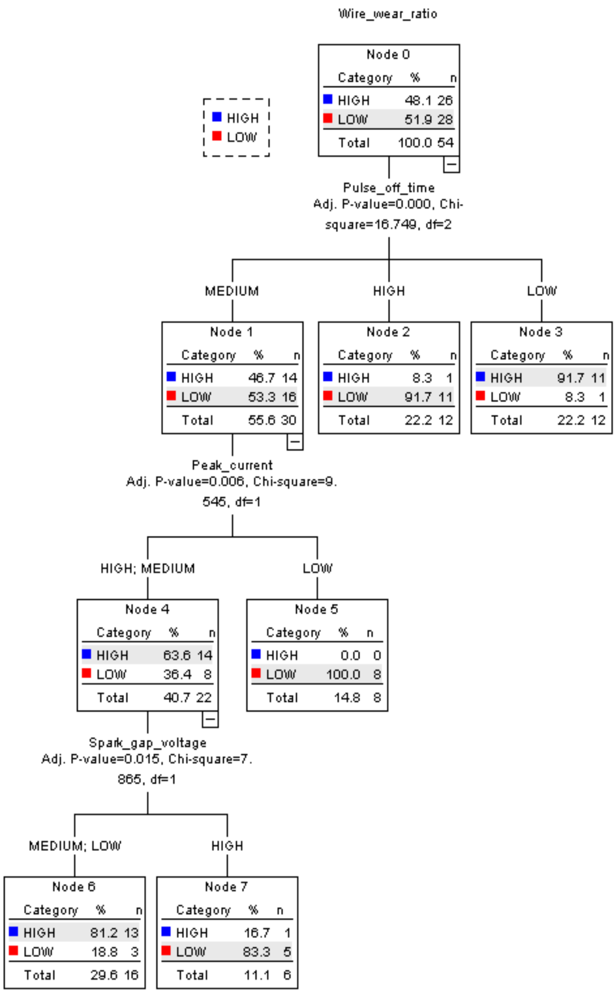

Fig. 9. CHAID algorithm-based decision tree for WWR

An optimal parametric mix of low or moderate T_{off}, high I_P, low or moderate T_{on} and moderate SV was identified by Kumar et al. (2013) for attaining lower WWR, which almost corroborates the decision tree-based observations.

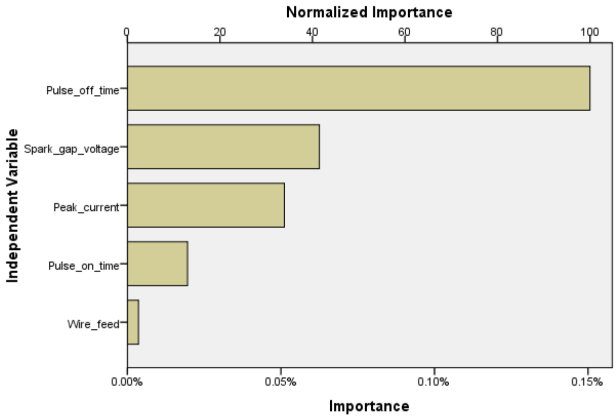

Fig. 10. Importance of WEDM process parameters on WWR

In Table 3, a comparison of the classification accuracies of CART and CHAID algorithms for all the four WEDM responses is provided. From this table, it can be noted that for MR response, CART algorithm can perfectly predict both of its low and high values. For this algorithm, the classification accuracies for high and low SR values are 92.3% and 96.4% respectively. Similarly, using CART algorithm, high and low DD values can be predicted with accuracies of 96.2% and 92.9% respectively. For WWR response, CART algorithm can respectively predict the corresponding high and low values with 92.30% and 89.28% accuracies. Thus, CART algorithm can almost perfectly predict both the high and low values of all the WEDM responses, although it has a slightly greater likelihood to accurately envisage high values of the responses.

In case of CHAID algorithm, high values of MR and SR are respectively predicted with 100% and 92.3% accuracies. It has prediction accuracies of 96.2% and 89.3% respectively for high and low DD values. For this algorithm, the classification accuracy for low WWR is the least (85.7%). Based on the overall classification accuracies of both these algorithms, it can be concluded that CART algorithm outperforms CHAID algorithm for all the four responses.

Table 3
Classification accuracies for MR, SR, DD and WWR using CART and CHAID algorithms

Response	CART				CHAID			
MR		Predicted				Predicted		
	Observed	High (> 0.74 mm/min)	Low (≤ 0.74 mm/min)	Percent correct	Observed	High (> 0.74 mm/min)	Low (≤ 0.74 mm/min)	Percent correct
	High (> 0.74 mm/min)	27	0	100	High (> 0.74 mm/min)	27	0	100
	Low (≤ 0.74 mm/min)	0	27	100	Low (≤ 0.74 mm/min)	1	26	96.3
	Overall percentage	50	50	100	Overall percentage	51.9	48.1	98.1
SR		Predicted				Predicted		
	Observed	High (> 2.68 µm)	Low (≤ 2.68 µm)	Percent correct	Observed	High (> 2.68 µm)	Low (≤ 2.68 µm)	Percent correct
	High (> 2.68 µm)	24	2	92.3	High (> 2.68 µm)	24	2	92.3
	Low (≤ 2.68 µm)	1	27	96.4	Low (≤ 2.68 µm)	2	26	92.9
	Overall percentage	46.3	53.7	94.4	Overall percentage	48.1	51.9	92.6
DD		Predicted				Predicted		
	Observed	High (152 µm)	Low (≤ 152 µm)	Percent correct	Observed	High (152 µm)	Low (≤ 152 µm)	Percent correct
	High (> 152 µm)	25	1	96.2	High (> 152 µm)	25	1	96.2
	Low (≤ 152 µm)	2	26	92.9	Low (≤ 152 µm)	3	25	89.3
	Overall percentage	50	50	94.5	Overall percentage	51.9	48.1	92.6
WWR		Predicted				Predicted		
	Observed	High (> 0.079)	Low (≤ 0.079)	Percent correct	Observed	High (> 0.079)	Low (≤ 0.079)	Percent correct
	High (> 0.079)	24	2	92.30	High (> 0.079)	24	2	92.3
	Low (≤ 0.079)	3	25	89.28	Low (≤ 0.079)	4	24	85.7
	Overall percentage	50	50	90.80	Overall percentage	51.9	48.1	88.9

Conclusions

In this paper, two data mining-based classification techniques, i.e. CART and CHAID algorithms, are employed to generate the corresponding decision trees for analyzing a past WEDM experimental dataset. It is observed that in the WEDM process, T_{on} is the most important input parameter affecting almost all the responses, followed by T_{off} and I_P. On the other hand, WF and WT contribute least towards attainment of the target response values.

During T_{on}, actual machining in the WEDM process usually takes place. An increment in T_{on} causes the machining process to be faster with higher MRR and poor quality of the machined surface.

On the other hand, during T_{off}, the dielectric fluid in the WEDM process is re-ionized. An insufficient T_{off} time may lead to erratic cycling, thereby slowing down the machining process. With increased T_{off}, MRR is gradually decreased, primarily due to reduced spark discharge energy. Higher I_P causes availability of larger discharge energy resulting in more material being removed from the workpiece surface. Thus, a mix of higher T_{on} with lower T_{off} results in more sparking time, thus leading to increased MRR which is of primary importance in any of the machining processes.

The induction rules extracted from the decision trees lead to the following conclusions:

1. For achieving higher MR, high values of T_{on} and I_P, and low values of T_{off} and SV need to be set.
2. To attain lower SR of the machined components, low or medium T_{on}, high T_{off}, low or medium I_P and high SV are recommended. WF and WT play no significant roles on SR.
3. A mix of low or medium T_{on}, long T_{off}, small I_P and high SV is responsible for attainment of lower DD.
4. Low T_{off}, high or medium T_{on}, high I_P and low or medium SV are accountable for lower WWR.
5. The CART algorithm supersedes CHAID algorithm with respect to both overall classification accuracy and prediction risk. But, both these algorithms can almost perfectly envisage high and low values of all the considered responses for the WEDM process.

Thus, these data mining tools can be effectively applied to all the traditional and non-traditional machining processes to investigate the contributions of varied input parameters on the responses and identify the most suitable parametric combinations for exploring their fullest machining potential. But, the developed decision trees are highly unstable compared to other decision predictors as a small variation in data may result in a major change in the structure of the decision trees, conveying different pictures from the expected ones.

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